The Relation between Time-Series and Cross-Sectional Effects of Idiosyncratic Variance on Stock Returns in G7 Countries

Authors	Hui Guo, and Robert Savickas
Working Paper Number	2006-036A
Creation Date	May 2006
Citable Link	https://doi.org/10.20955/wp.2006.036
Suggested Citation	Guo, H., Savickas, R., 2006; The Relation between Time-Series and Cross-Sectional Effects of Idiosyncratic Variance on Stock Returns in G7 Countries, Federal Reserve Bank of St. Louis Working Paper 2006-036. URL https://doi.org/10.20955/wp.2006.036

The Relation between Time-Series and Cross-Sectional Effects of Idiosyncratic Variance on Stock Returns in G7 Countries

Hui Guo[a] and Robert Savickas[b*]

This Version: May 22, 2006

[*a] Corresponding Author: Research Division, Federal Reserve Bank of St. Louis (P. O. Box 442, St. Louis, MO, 63166-0442, E-mail: hui.guo@stls.frb.org); and [b] Department of Finance, George Washington University (2023 G Street, N.W. Washington, DC 20052, E-mail: Savickas@gwu.edu). We thank Yakov Amihud for suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect the official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

The Relation between Time-Series and Cross-Sectional Effects of Idiosyncratic Variance on Stock Returns in the G7 Countries

Abstract

This paper suggests that CAPM-based idiosyncratic variance (IV) correlates negatively with future stock returns because it is a proxy for loadings on discount-rate shocks in Campbell's (1993) ICAPM. The ICAPM also implies that there are important links between the time-series and cross-sectional IV effects. For example, the coefficients on conditional stock market variance and value-weighted average IV obtained from the time-series regressions reflect loadings on stock market returns and discount-rate shocks, respectively; therefore, they should help explain the cross section of stock returns. Moreover, we expect a close relation between the IV and book-to-market effects because recent studies show that the latter also reflects intertemporal pricing. These conjectures are strongly supported by the G7 countries' data.

Keywords: Stock Return Predictability, Average Idiosyncratic Volatility, Stock Market Volatility, the Cross Section of Stock Return, Value Premium, CAPM, ICAPM.

JEF number: G1.

The capital asset pricing model (CAPM) indicates that investors should not be compensated for bearing idiosyncratic risk—the component of asset returns that is not explained by the aggregate market movement. However, recent studies show that IV—realized variance of CAPM-based idiosyncratic shocks—has two important effects on expected stock returns in the post-1963 U.S. data.[1] First is the cross-sectional effect. Easley et al. (2002) and Ang et al. (2006a), among others, find that high IV stocks have lower expected returns than low IV stocks. Second is the time-series effect. Guo and Savickas (2006) aggregate IV across individual stocks and find that the value-weighted average IV (VWAIV) correlates negatively with future stock market returns when used in conjunction with realized stock market variance (MV); consistent with CAPM, MV is positively related to future stock market returns.

The negative IV effects seem puzzling because many asset pricing models, e.g., Levy (1978), Merton (1987), and Malkiel and Xu (2002), predict a positive relation between the idiosyncratic risk and return.[2] One possibility is that IV is a proxy for the divergence of opinion (e.g., Shalen, 1993), which leads a stock to be over-valued initially and to suffer capital losses eventually in the presence of binding short-sales constraints (Miller, 1977). However, Miller's hypothesis cannot fully account for the observed time-series and cross-sectional IV effects.[3] Ang et al. (2006a) show that their results are robust

[1] These studies also use the Fama and French (1993) 3-factor model to adjust for systematic risk and find essentially the same results. For brevity, we only focus on CAPM-based IV in this paper.
[2] Fu (2005) and Spiegel and Wang (2005) estimate idiosyncratic volatility using an EGARCH model and find a positive relation between conditional idiosyncratic risk and return. Their findings are not necessarily inconsistent with those documented by Ang et al. (2006a) because, as we will explain later, the CAPM-based IV has two components: (1) variance of the risk factor(s) omitted from CAPM and (2) variance of the true idiosyncratic shock. This paper suggests that IV used by Ang et al (2006a) is a proxy for loadings on a systematic risk factor—i.e., the discount-rate shock in Campbell's (1993) ICAPM—which is omitted from CAPM. By contrast, Fu (2005) and Spiegel and Wang (2005) interpret their results as support for Merton's (1987) model, i.e., their IV measures are proxies for variance of the true idiosyncratic shock.
[3] The empirical evidence on Miller's (1977) hypothesis is also mixed. Some authors, e.g., Diether et al. (2002), Asquith et al. (2005), and Boehme et al. (2006), document a negative relation between proxies for the divergence of opinion and expected stock returns, especially for stocks that are likely to have binding

to the control for the dispersion of IBES analysts' earning forecasts, which Diether et al. (2002) use to proxy for the divergence of opinion. Also, Miller's hypothesis doesn't explain why VWAIV forecasts stock market returns only when combined with MV.

This paper suggests that IV forecasts stock returns because it proxies for loadings on systematic risk omitted from CAPM. As we show in the next section, in Campbell's (1993) ICAPM, the CAPM-based IV of stock *i* is equal to $\beta_{i,DR}^2 \varepsilon_{DR,t}^2 + \varepsilon_{i,t}^2$, where $\beta_{i,DR}$ is the loading on the discount-rate shock, $\varepsilon_{DR,t}^2$ is realized variance of the discount-rate shock that is orthogonal to stock market returns, and $\varepsilon_{i,t}^2$ is realized variance of the true idiosyncratic shock. Note that $\beta_{i,DR}$ is negative because an unexpected increase in the discount rate leads to an immediate fall in stock prices; therefore, if $\varepsilon_{i,t}^2$ is negligible, IV is negatively correlated with $\beta_{i,DR}$.[4]

In Campbell's ICAPM, the expected excess return on any asset, $E_t(R_{i,t+1})$, is determined by its covariances with stock market returns and the discount-rate shock

(1) $$E_t(R_{i,t+1}) = \gamma \beta_{i,M} \sigma_{M,t}^2 + (\gamma - 1)\beta_{i,DR} \sigma_{DR,t}^2,$$

where γ is the coefficient of relative risk aversion; $\sigma_{M,t}^2$ is conditional stock market variance; $\sigma_{DR,t}^2$ is conditional variance of the discount-rate shock; and $\beta_{i,M}$ is the loading on stock market returns. If γ is greater than 1, which appears to apply here, equation (1) predicts that *all else equal*, $\beta_{i,DR}$ is positively related to expected stock returns. Thus, the negative cross-sectional IV effect might reflect the negative relation between IV and

---

short-sales constraints. However, other authors, e.g., Chen et al. (2002) and Doukas et al. (2006), find little support for Miller's hypothesis.

[4] If the true idiosyncratic shock is not negligible, the CAPM-based IV is a noisy measure of loadings on the discount-rate shock.

$\beta_{i,DR}$, as we explained above. Moreover, as we also show in the next section, VWAIV is negatively related to future stock returns, including the aggregate market return, because it is a proxy for $\sigma^2_{DR,t}$ in equation (1); similarly, MV is positively related to future returns because it proxies for $\sigma^2_{M,t}$. Thus, Campbell's ICAPM also explains why MV and VWAIV forecast stock market returns only jointly but not individually.

Equation (1) reveals three important links between the time-series and cross-sectional IV effects. First, because the discount-rate shock has only temporary effects on stock prices, stocks with high IV and thus strong sensitivity to the discount-rate shock should have a larger portion of predictable variation than stocks with low IV. Second, the coefficients on VWAIV, which are negative for all stocks, should be smaller for high IV stocks than low IV stocks. Third, and more importantly, the coefficients on MV and VWAIV help explain the cross section of stock returns because they reflect loadings on stock market returns and discount-rate shocks, respectively. These implications, which are the main focus of our empirical analysis, help us distinguish Campbell's ICAPM from the alternative theories, e.g., Miller (1977) and Merton (1987). Also, empirical support for the ICAPM implications alleviates the concern about data mining.

We use three sets of data. First is a modern U.S. sample over the period 1963 to 2005 that is similar to that used by Ang et al. (2006a) and Guo and Savickas (2006); and we confirm the finding of a negative cross-sectional IV effect. As a robustness check, we also analyze a long U.S. sample over the period 1926 to 2005 and the international data of G7 countries over the period 1973 to 2003.[5] We find that, after controlling for loadings on the market risk, high IV stocks have lower expected returns than low IV stocks in the

[5] We use CRSP (the Center for Research in Security Prices) data for both the modern and long U.S. samples. The daily stock returns data, which we use to construct realized variance, were recently extended backward from July 1962 to January 1926.

long U.S. sample as well as many other G7 countries. These out-of-sample tests suggest that the cross-sectional IV effect is pervasive and cannot be attributed to data mining.

We find strong support for the three ICAPM implications using all three sets of data. For the two U.S. samples, we sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by IV. Both MV and VWAIV have significant predictive power for the portfolio returns, especially in the modern sample. For all 25 portfolios, the correlation with future portfolio returns is positive for MV but negative for VWAIV. Consistent with the first two ICAPM implications, R^2 and the coefficients on VWAIV increase monotonically from low IV stocks to high IV stocks. More importantly, as hypothesized, both VWAIV and MV are positively priced in the Fama and MacBeth (1973) cross-sectional regressions; they account for over 60% and 80% of cross-sectional variation of average portfolio returns in the modern and long U.S. samples, respectively.

For the international data, we sort stocks of each of the G7 countries equally into five portfolios by IV. Interestingly, for most of the other G7 countries, trading profits of buying low IV stocks and selling high IV stocks comove strongly with their U.S. counterpart; they are also predictable by U.S. MV and VWAIV. This result confirms that the IV effects are pervasive and cannot be easily diversified away. It also suggests that the U.S. risk factors have important influence on international stock markets. Indeed, in the Fama and MacBeth (1973) regressions, U.S. MV and VWAIV jointly account for about 80% of cross-sectional variation of average returns on the 35 international portfolios sorted by IV, with 5 quintiles for each of the G7 countries.

To further substantiate the argument that the IV effects reflect systematic risk, we construct a mimicking factor, IVF, which is the return on a portfolio that is short in high

IV stocks and long in low IV stocks. Recall that we hypothesize that high IV stocks have lower expected returns than low IV stocks because the former are more sensitive to the discount-rate shock. Thus, we expect that loadings on IVF help explain the cross section of stock returns because it mimics the discount–rate shock. Indeed, when used in conjunction with the market and size factors, IVF is positively and significantly priced in the cross-sectional regressions for all three sets of data, with the cross-sectional R^2 s similar to those obtained by the specification in which we use the coefficients on MV and VWAIV to proxy for loadings on market returns and discount-rate shocks, respectively.

Lastly, we note that the cross-sectional IV effect is related to the well documented book-to-market effect (e.g., Fama and French, 1993). This is because Campbell and Vuolteenaho (2004) find that growth stocks have lower expected returns than value stocks because the former is more sensitive to the discount-rate shock. This conjecture, which poses an out-of-sample test for our main hypotheses, is again strongly supported by the data. In the modern U.S. sample, IVF is closely correlated with the value factor (HML) of the Fama and French (1993) 3-factor model, with a correlation coefficient of about 45%. More importantly, IVF has explanatory power for the 25 Fama and French portfolios almost identical to that of HML; for example, the cross-sectional R^2 is about 83% for IVF and 80% for HML. Similarly, we find that VWAIV also has significant explanatory power for the 25 Fama and French portfolios. Our results suggest that the book-to-market effect does reflect loadings on the discount-rate shock.

Ang et al. (2006b) and Guo and Savickas (2005) also document significant cross-sectional and time-series IV effects, respectively, in international stock markets. These authors suggest that their results might reflect systematic risk; however, they don't fully characterize and test the relation between the time-series and cross-sectional IV effects, as we do in this paper.

The remainder of the paper is organized as follows. We explain the theoretical framework in Section I and discuss the data in Section II. We investigate the link between the time-series and cross-sectional IV effects in U.S. data in Section III and present international evidence in Section IV. We offer some concluding remarks in Section V.

I. Theoretical Framework

A. Campbell's ICAPM

If stock returns are predictable, Campbell and Shiller (1988) decompose the unexpected excess stock market return into the cash-flow shock ($N_{CF,t+1}$) and the discount-rate shock ($N_{DR,t+1}$):

(2) $$R_{t+1} - E_t(R_{t+1}) = N_{CF,t+1} - N_{DR,t+1}.$$

Equation (2) shows that stock prices fall if there is either a negative shock to cash flows or a positive shock to discount rates. Campbell and Vuolteenaho (2004) emphasize that discount-rate shocks are not as risky as cash-flow shocks because the two types of shocks have different long-run effects on stock prices. The positive discount-rate shock is associated with an improvement in investment opportunities, i.e., higher expected future stock returns. By contrast, investment opportunities don't change with the cash-flow shock. Thus, discount rates are a measure of investment opportunities, and the expected excess return on any asset is determined by its conditional covariances with the excess stock market return, $\sigma_{i,M,t}$, and the discount-rate shock, $\sigma_{i,DR,t}$:

(3) $$E_t(R_{i,t+1}) = \gamma\sigma_{i,M,t} + (\gamma - 1)\sigma_{i,DR,t}.$$

Note that we obtain equation (1) from equation (3) by assuming that factor loadings are constant across time. Also, because $\beta_{M,M}$ is equal to 1, we can write the expected excess stock market return as

(4) $$E_t(R_{t+1}) = \gamma\sigma^2_{M,t} + (\gamma - 1)\beta_{M,DR}\sigma^2_{DR,t}.$$

The coefficient $\beta_{M,DR}$ is negative because an increase in expected stock market returns leads to an immediate fall in stock prices and thus a negative stock market return. That is, in Campbell's (1993) ICAPM, the stock market serves as a hedge for changes in investment opportunities. Therefore, if γ is greater than 1, which appears to apply here, the coefficient on conditional variance of the discount-rate shock should be negative. This result has an intuitive interpretation. The discount-rate risk is over compensated in CAPM because it doesn't recognize that discount-rate shocks are not as risky as cash-flow shocks. Therefore, the negative effect of conditional discount-rate variance on expected stock market returns serves as a correction for the mispricing in CAPM.

Similarly, it is arguable that $\beta_{i,DR}$ is likely to be negative for individual stocks because all else equal, an increase in discount rates lowers stock prices. Therefore, equation (1) suggests that, if we hold the loading on stock market returns ($\beta_{i,M}$) constant, stocks with high loadings on the discount-rate shock tend to have lower expected returns than stocks with low loadings. Again, this result reflects the fact that discount-rate shocks are not as risky as cash-flow shocks. In the next subsection, we show that the CAPM-based IV has negative effects on expected stock returns because of its negative correlation with the loadings on the discount-rate shock.

B. The CAPM-Based IV and Loadings on Discount-Rate Shocks

We construct the CAPM-based idiosyncratic shock by regressing individual excess stock returns on excess stock market returns:

(5) $$R_{i,t} = \hat{\beta}_{i,t} R_t + \eta_{i,t},$$

where $\hat{\beta}_{i,t}$ is the estimated loading on stock market returns in period *t*. Realized CAPM-based IV for stock *i* is[6]

(6) $$IV_{i,t} = \eta_{i,t}^2 .$$

We aggregate equation (6) across all stocks and obtain CAPM-based value-weighted average idiosyncratic variance

(7) $$VWAIV_t = \sum_{i=1}^{N_t} \frac{C_{i,t}}{\sum C_{i,t}} IV_t ,$$

where N_t is the number of stocks in period *t* and $C_{i,t}$ is market capitalization at the end of the period *t*-1. Realized stock market variance is

(8) $$MV_t = R_t^2 .$$

In the remainder of this subsection, we show that $IV_{i,t}$ predicts the cross section of stock returns (e.g., Ang et al. 2006a) because in Campbell's ICAPM it proxies for loadings on the discount-rate shock. Also, MV_t and $VWAIV_t$ jointly forecast stock market returns (e.g., Guo and Savickas, 2006) because they are proxies for conditional stock market variance and conditional discount-rate variance, respectively.

---

[6] For ease of illustration, in equation (6) we assume that realized IV for period *t* is the squared idiosyncratic shock of period *t*. However, in our empirical implementation, realized IV is the sum of squared daily idiosyncratic shocks in period *t*. This clarification also applies for realized stock market variance in equation (8), which we will discuss below.

For illustration, we define $R_{DR,t}$ as the excess return on a hedge portfolio, i.e., $R_{DR,t}$ has perfect correlation with the change in investment opportunities— $N_{DR,t}$. Therefore, we can write the ex-post return on any asset as

(9) $$R_{i,t} - E_{t-1}(R_{i,t}) = \beta_{i,M}(R_t - E_{t-1}R_t) + \beta_{i,DR}(R_{DR,t} - E_{t-1}R_{DR,t}) + \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ is the true idiosyncratic shock that is orthogonal to stock market returns and the discount-rate shock. Stock market returns and the discount-rate shock are correlated:

(10) $$R_{DR,t} - E_{t-1}(R_{DR,t}) = \beta_{M,DR}(R_t - E_{t-1}R_t) + \varepsilon_{DR,t}.$$

Equations (5), (9) and (10) imply that realized CAPM-based IV is

(11) $$IV_{i,t} = \beta^2_{i,DR}\varepsilon^2_{DR,t} + \varepsilon^2_{i,t}.$$

For ease of illustration, we first assume that the true idiosyncratic shock $\varepsilon_{i,t}$ is negligible; we will discuss its effects on asset returns later. In this case, equation (11) indicates that $IV_{i,t}$ is negatively related to $\beta_{i,DR}$ because $\beta_{i,DR}$ is negative. Therefore, *all else equal*, stocks with high IV tend to have lower loadings on the discount-rate shock and thus lower expected returns than stocks with low IV.

The link between $IV_{i,t}$ and $\beta_{i,DR}$ holds only approximately because variance of the true idiosyncratic shock, $\varepsilon^2_{i,t}$, is unlikely to be negligible. Depending on their relative importance, $IV_{i,t}$ could be a proxy for either loadings on the discount-rate shock or variance of the true idiosyncratic shock. For example, variance of the true idiosyncratic variance tends to be larger for small stocks than large stocks, this observation helps explain why Ang et al. (2006a, 2006b) as well as this paper document stronger cross-sectional IV effects using the value-weighted portfolio return than its equal-weighted counterpart. It might also explain why Spiegel and Wang (2005) and Fu (2005) find a positive relation between conditional idiosyncratic risk and return by using alternative measures of idiosyncratic variance. Nevertheless, this paper finds that realized IV used by Ang et al. (2006a) and Guo and Savickas (2006) provides a good proxy for loadings on the discount-rate shock.

Substituting equation (11) into equation (7), we obtain

(12) $$VWAIV_t = \mu_{DR,t} + \phi_{DR,t}\varepsilon_{DR,t}^2,$$

where $\mu_{DR,t} = \sum_{i=1}^{N}\frac{C_{i,t}}{\sum C_{i,t}}\varepsilon_{i,t}^2$ and $\phi_{DR,t} = \sum_{i=1}^{N}(\frac{C_{i,t}}{\sum C_{i,t}}\beta_{i,DR}^2)$. Thus, VWAIV proxies for the variance of the orthogonalized discount-rate shock if, as we assume in this paper, $\mu_{DR,t}$ and $\phi_{DR,t}$ are constant across time. Equation (10) and (12) imply that realized discount-rate variance (DRV) is

(13) $$DRV_t = \beta_{M,DR}^2 MV_t + \frac{VWAIV_t}{\phi_{DR}} + \frac{\mu_{DR}}{\phi_{DR}}.$$

Because they are serially correlated, we use realized discount-rate variance (DRV), realized stock market variance (MV), and realized value-weighted idiosyncratic variance (WVAIV) to proxy for their conditional values. After some rearrangements, we obtain the ex-post version of equation (1)

(14) $$R_{i,t+1} = \frac{(\gamma-1)\beta_{i,DR}\mu_{DR}}{\phi_{DR}} + [\gamma\beta_{i,M} + (\gamma-1)\beta_{i,DR}\beta_{M,DR}^2]MV_t + \frac{(\gamma-1)\beta_{i,DR}}{\phi_{DR}}VWAIV_t + \xi_{i,t+1}.$$

The excess stock market return is also a linear function MV and VWAIV:

(15) $$R_{t+1} = \frac{(\gamma-1)\beta_{M,DR}\mu_{DR}}{\phi_{DR}} + [\gamma + (\gamma-1)\beta_{M,DR}^3]MV_t + \frac{(\gamma-1)\beta_{M,DR}}{\phi_{DR}}VWAIV_t + \xi_{M,t+1}.$$

Equation (15) shows that the negative relation between VWAIV and future stock market returns reflects the fact that VWAIV is a proxy for conditional discount-rate variance, i.e., $\beta_{M,DR}$ is negative. It also suggests that MV and VWAIV forecast stock returns only jointly but not individually because the discount-rate shock and the cash-flow shock are priced differently.

C. Refutable Implications of Campbell's ICAPM

We have shown that the CAPM-based IV has cross-sectional (Ang et al. 2006a) and time-series (Guo and Savickas 2006) effects on expected stock returns possibly because in Campbell's ICAPM it proxies for loadings on the discount-rate shock. To formally test this hypothesis, we propose three refutable implications.

First, the discount-rate shock has only a temporal effect on stock prices. If the CAPM-based IV is a proxy for loadings on the discount-rate shock, stocks with high IV and thus strong sensitivity to the discount-rate shock have a larger portion of predictable variation than stocks with low IV.

Second, if IV is a proxy for loadings on the discount-rate shock and if VWAIV is a proxy for conditional discount-rate variance, equation (14) shows that the coefficients on VWAIV are negative because $\beta_{i,DR}$ is negative. More importantly, the coefficients on VWAIV are smaller for high IV stocks than low IV stocks.

Third, in equation (14), the coefficients on MV and VWAIV reflect loadings on stock market returns and the discount-rate shock, respectively. Therefore, they should help explain the cross section of stock returns. Also, because both stock market risk and the discount-rate shock carry a positive risk premium in Campbell's ICAPM, both MV and VWAIV should be positively priced in the cross-sectional regressions.

Moreover, equation (11) suggests that all else equal, high IV stocks tend to have lower loadings on the discount-rate shock than do low IV stocks. Therefore, the return on a hedge portfolio that is long in low IV stocks and short in high IV stocks, which we dub IVF, should be closely correlated with the discount-rate shock. In particular, IVF is a proxy for the risk factor $R_{DR,t}$ in equation (9), which we will also investigate empirically. Note that equations (9) and (14) are motivated by the same economic theory, i.e., Campbell's ICAPM, although we estimate loadings on the risk factors using different variables in the two equations. Therefore, we expect to find qualitatively same results by using the two specifications. For example, IVF is positively priced in the cross-sectional regressions because the discount-rate risk carries a positive risk premium in the ICAPM.

II. Data

We use stock return data from CRSP for the U.S. over the period January 1926 to December 2005 and Datastream for the other G7 counties over the period January 1973 to December 2003. All returns are denoted in local currencies. We obtain the monthly risk-free rate data from CRSP for the U.S. and the IFS (the International Financial Statistics) for the other G7 countries. The risk-free rate is unavailable at the daily frequency; we assume that the daily risk-free rate is constant within a month and compounds to the monthly risk-free rate. The daily excess stock return is the difference between the daily stock return and the daily risk-free rate.

We follow Ang et al. (2006a) in the construction of portfolios sorted by the CAPM-based IV. At the beginning of each month, we calculate realized IV, which is the sum of squared daily CAPM-based idiosyncratic shocks in the previous month. We then sort stocks equally by IV into quintile portfolios, for example; the first quintile includes stocks with the lowest IV and the fifth quintile includes stocks with the highest IV. We hold these portfolios for one month and rebalance them at the beginning of the next month, and so on. Unless otherwise indicated, we follow Ang et al. and use the value-weighted portfolio returns through the paper. As in Guo and Savickas (2006), we aggregate IV across the 500 largest stocks with value weighting to construct VWAIV; we find essentially the same results by using all CRSP common stocks. Lastly, following Merton (1980) and Andersen et al. (2003), MV is the sum of squared daily excess stock market returns in a given period.

We have imposed some filters for the Datastream data for potential errors. As we show in Section IV, for the U.S., the imposition of these filters produces the cross-sectional IV effect very similar to that obtained from CRSP; also, Guo and Savickas (2005) document a similar finding for the VWAIV. These results confirm the appropriateness of these filters. (1) The return index (Datastream variable RI) is rounded off to the nearest tenth and this rounding introduces substantial errors in returns of low RI stocks. Therefore, if the return index of a stock is below 3 in a day, we set the corresponding return to a missing value for that day.[7] (2) If the return on a stock is greater than 300 percent in a day, we set that return to a missing value. (3) If the absolute value of changes in capitalization is more than 50 percent in one day, the return for this stock is set to a missing value on that day. (4) If the price of a stock falls by more than 90 percent in a day and it has increased by more than 200 percent within the previous 20 days (approximately a trading month), we set the returns between the two dates to missing values. (5) If the price of a stock increases by more than 100 percent in a day and has

[7] The beginning RI for each stock is set at 100 by DataStream. Thus, an RI of 3 or below indicates that the firm has lost 97% or more of its value over its life.

decreased by more than 200 percent within the previous 20 days, we set the returns between the two dates to missing values.

We confirm that MV and VWAIV have significant predictive power for excess stock market returns in both the modern and long U.S. samples; for brevity, these results are omitted here but are available on request.

III. Links between Time-Series and Cross-Sectional IV Effects in U.S. Data

A. The Modern Sample: 1963 to 2005

We first discuss the empirical results for the modern sample over the period 1963 to 2005, which is similar to that used by Ang et al. (2006a) and Guo and Savickas (2006). In the next subsection, we will show that the results are qualitatively the same for the long sample spanning the period 1926 to 2005.

Many authors, e.g., Campbell et al. (2001) and Pastor and Veronesi (2003), find that small stocks have substantially higher IV than do large stocks. To illustrate that the IV effect doesn't only concentrate in small stocks, we explicitly control for size when forming portfolios. In particular, as in Ang et al. (2006a), we first sort stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by IV. Also, because Ghysels et al. (2005) show that realized variance is a function of long distributed lags of past daily stock returns, we follow Guo and Savickas (2006) and use quarterly MV and VWAIV in the forecasting regressions.[8]

[8] Goyal and Santa-Clara (2003) find a positive relation between equal-weighted average IV and future stock market returns in monthly data; however, Bali et al. (2005) show that their results are sensitive to the weighting scheme and the slight extension of sample period.

We also convert monthly portfolio returns into quarterly returns by simple compounding.[9]

We first confirm the main results by Ang et al. (2006a) by showing that there is a significant cross-sectional IV effect in the updated modern sample. Panel A of Table 1 reports the average excess return for each of the 25 portfolios sorted by size and IV. S1 is the quintile of stocks with the smallest market capitalization and S5 is the quintile of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile of stocks with the lowest IV and IV5 is the quintile of stocks with the highest IV. Holding size constant, the quintile of the stocks with highest IV has substantially lower average excess returns than do the other IV quintiles.

Although the pattern in panel A of Table 1 is suggestive, it is not a formal test because Campbell's ICAPM predicts that low IV stocks have higher expected returns than high IV stocks *after controlling for loadings on the market risk*. To address this issue, panel B reports the CAPM-based alphas for the return on a hedge portfolio that is long in IV1 and short in IV5 within each size quintile. Alphas are significantly positive for the second to fifth size quintiles and are marginally significant for the first size quintile. Interestingly, alphas are noticeably larger than the differences in raw returns. This is because, as we will show below, loadings on the market risk are actually lower for IV1 than IV5. These results confirm the finding by Ang et al. (2006a) that portfolios sorted by IV pose a challenge to CAPM.

We then investigate whether the cross-sectional IV effect reflects loadings on the discount-rate shock by testing the three ICAPM implications. We address the first two

[9] As a robustness check, we also form portfolios according to the previous quarter's IV and rebalance the portfolios every quarter; the portfolios constructed from quarterly data produce essentially the same results. For brevity, these results are not reported here but are available on request.

implications by presenting the OLS (ordinary least squares) estimation results of regressing one-quarter-ahead excess portfolio returns on MV and VWAIV. Before turning to the discussion of the ICAPM, we briefly explain why CAPM fails to explain the cross-sectional IV effect. Panel C of Table 1 shows that for all 25 portfolios, the coefficients on MV are positive and statistically significant at least at the 10% level. Within each size quintile, the coefficients on MV increase monotonically from IV1, the quintile of stocks with the lowest IV, to IV5, the quintile of stocks with the highest IV. Because the coefficients on MV are proportional to loadings on stock market returns, these results demonstrate that CAPM cannot explain the IV effect because high IV stocks actually have higher loadings on stock market returns than do low IV stocks.

By contrast, panel D of Table 1 shows that Campbell's ICAPM helps explain why high IV stocks have lower expected returns than do low IV stocks. The coefficients on VWAIV are negative for all 25 portfolios; they are also statistically significant at least at the 10% level in most cases. Consistent with the second refutable ICAPM implication, within each size quintile, the coefficients on VWAIV decreases monotonically from IV1 to IV5. Recall that the coefficients on VWAIV reflect loadings on the discount-rate shock, and the discount-rate shock carries a positive risk premium. Therefore, the results in panel D suggest that high IV stocks have lower expected returns than low IV stocks because high IV stocks have lower loadings on the discount-rate shock.

Panel G of Table 1 provides further support for the hypothesis that high IV stocks are more sensitive to the discount-rate shock than are low IV stocks. In particular, consistent with the first refutable ICAPM implication, within each size quintile, R^2—a measure of the portion of predictable variation in the portfolio returns—increases substantially from IV1 to IV5. For example, across the size quintiles, the average R^2 is 1% for the IV1, compared with 10% for IV5.

To quantify the effect of the discount-rate shock on the cross-sectional IV effect, panel H of Table 1 investigates the third refutable ICAPM implication whether the coefficients on MV and VWAIV help explain the cross section of stock returns. We use the Fama and MacBeth (1973) procedure in the cross-sectional regression. For each quarter, we regress the 25 excess portfolio returns on the coefficients of MV and VWAIV obtained from the time-series regressions, as reported in panels C and D, respectively. The time-series averages of coefficients on MV and VWAIV obtained from the cross-sectional regressions are the risk premia associated with the stock market risk and the discount-rate risk, respectively. We report two t-statistics for the estimated risk premia. The first one is calculated using the standard deviation of the time-series average, as proposed by Fama and MacBeth (in parentheses). The second one is calculated using the standard error advocated by Shanken (1992), which accounts for estimation errors in the coefficients on MV and VWAIV obtained from the first-pass time-series regressions (in squared brackets).

First row of panel H, Table 1 provides strong support for the third refutable ICAPM implication. The risk premium on VWAIV is positive; and it is also statistically significant at the 1% level, according to both the Fama and MacBeth (1973) and Shanken (1992) standard errors. Moreover, consistent with ICAPM, the risk premium on MV is also positive and statistically significant at the 5% level, according to both measures of the standard errors. These results clearly demonstrate that, as suggested by equation (1), CAPM fails to explain the cross section of stock returns because of an omitted variable problem, i.e., the omission of the discount-rate shock. Overall, the two variables account for about 63% of cross-sectional variation in average portfolio returns.[10]

Lastly, we investigate whether IVF—the equal-weighted average of the return difference between IV1 and IV5 across all size quintiles—is a proxy for the hedge factor, $R_{DR,t}$, in equation (9). This conjecture is plausible because in panel D of Table 1 we show that high IV stocks are indeed more sensitive to the discount-rate shock than low IV stocks. In the cross-sectional regression we also include the market (MKT) as well as size (SMB) factors obtained from Ken French at Dartmouth College. We include the size factor to control for the potential bias introduced by forming portfolios first by market capitalization. Also, the size factor might capture systematic risk that is not explained by MKT and IVF.

Recall that because equations (9) and (14) are motivated by the same economic theory, i.e., Campbell's ICAPM, we expect that the specification in equation (9) produces results similar to those based on the specification in equation (14), as reported in the first row of panel H, Table 1. This conjecture is confirmed by the results reported in the second row of panel H, Table 1. Both IVF and MKT are positively priced; they are also statistically significant at the 5% and 10% levels, respectively, according to the Shanken-corrected standard errors. We find that the size factor also carries a significantly positive risk premium. Overall, the three risk factors jointly account for about 54% of cross-sectional variation in average portfolio returns.

[10] The cross-sectional R^2 of 63% is admittedly low. One possibility is that the test has relatively low power because of the relatively short sample. As we will show in the next subsection, the cross-sectional R^2 increases substantially to about 81% in the long U.S. sample, in which we have much more observations.

To summarize, we find that the ICAPM implications are strongly supported by the U.S. data over the period 1963 to 2005. Moreover, Campbell's ICAPM accounts for a large portion of cross-sectional variation of average returns on portfolios sorted by IV. Our results suggest that the IV effects do reflect loadings on discount-rate shocks.

B. The Full Sample: 1926 to 2005

As a robustness check, we also test the ICAPM implications using the long U.S. sample over the period 1926 to 2005. Table 2 shows that the main results obtained from the long sample are essentially the same as those reported in Table 1 for the modern sample. First, the CAPM-based alphas for the return difference between IV1 and IV5 are always positive; they are significant at 10% level for smallest size quintile and at the 1% level for the other size quintiles (panel B). Therefore, the cross-sectional IV effect is not specific to the modern sample.[11] Second, the coefficients on MV are always positive; also, they are larger for high IV stocks than low IV stocks (panel C). This result illustrates why CAPM fails to explain the cross-sectional IV effect. Third, the coefficients on VWAIV are always negative; they are also smaller for high IV stocks than are low IV stocks (panel D). This result suggests that loadings on the discount-rate shock helps explain the cross-sectional IV effect. Fourth, high IV stocks tend to have a larger R^2 than low IV stocks (panel F). This result provides additional support for the hypothesis that high IV stocks are more sensitive to the discount-rate shock than low IV stocks. Lastly, and more importantly, panel H shows that loadings on both VWAIV and MV are positively and significantly priced in the cross-sectional regression and the associated R^2 is over 81%. Similarly, the risk factor IVF is also positively and significantly priced in

[11] We will show in the next section that there is a significant cross-sectional IV effect in the early sample over the period 1926 to 1962.

the cross-sectional regression and the associated R^2 is about 83%. Note that t-statistics and R^2s are noticeably higher than their counterparts reported in panel H of Table 1 for the modern sample. This is possibly because we improve the power of the tests by using a substantially longer sample here.[12]

To summarize, we find very similar results using the long U.S. sample, which again provides strong support for the hypothesis that high IV stocks have lower expected returns than low IV stocks because the former is more sensitive to discount-rate shocks.

C. Relation between the IV and Book-to-Market Effects

Many authors, e.g., Graham and Dodd (1934), Basu (1977, 1983), Ball (1978), and Rosenberg et al. (1985), have found that value stocks or stocks with a high book-to-market ratio have higher expected returns than growth stocks or stocks with a low book-to-market ratio. More importantly, the return difference between value and growth stocks remains significantly positive after we control for its loadings on the market risk. The book-to-market effect is one of the most prominent anomalies in the finance literature, and a number of explanations for it have been proposed.

In particular, Fama and French (1996) suggest that the book-to-market effect reflects intertemporal pricing, as in Merton's (1973) ICAPM.[13] This conjecture is also supported by recent empirical studies, e.g., Campbell and Vuolteenaho (2004), Brennan et al. (2004), and Petkova (2006). Moreover, Campbell and Vuolteenaho suggest that the

---

[12] However, MV and VWAIV are statistically insignificant for many portfolios. Also, R^2 is noticeably lower than those reported in Table 1. This is because the stock market crashes in the late 1920s and early 1930s generate large spikes in both MV and VWAIV as well as large volatility in portfolio returns.

[13] A partial list of the other possible explanations includes irrational pricing, e.g., Lakonishok et al. (1994); data snooping, e.g., MacKinlay (1995); and conditional CAPM, e.g., Lettau and Ludvigson (2001), Petkova and Zhang (2005), and Ang and Chen (2006). Recent authors, e.g., Berk et al. (1999), Gomes et al. (2003), Zhang (2005), and Lettau and Wachter (2006), have also developed equilibrium models to investigate the book-to-market effect.

book-to-market effect reflects the fact that growth stocks are more sensitive to the discount-rate shock than value stocks. Thus, one would expect a close relation between the IV and book-to-market effects, which we investigate here.[14]

If growth stocks are more sensitive to the discount-rate shock than value stocks, we can draw three ICAPM implications for the book-to-market effect that are similar to these for the cross-sectional IV effect. First, growth stocks have a higher portion of predictable variation than value stocks. Second, the coefficients on VWAIV are smaller for the growth stocks than do value stocks. Third, loading on MV and VWAIV helps explain the cross section of stock returns. To address these issues, we repeat the analysis of Tables 1 and 2 using 25 Fama and French portfolios sorted on size and the book-to-market ratio over the period 1963 to 2005.[15] We obtain the monthly portfolio returns data from Ken French at Dartmouth College and convert monthly returns to quarterly returns through simple compounding.

Panels C to G of Table 3 show that the first two ICAPM implications are supported by the data; for brevity, we omit the discussion of these results. Instead, we focus on the cross-sectional regression results, as reported in panel H. The first row shows that both MV and VWAIV are positively priced and VWAIV is also statistically significant at the 5% level according to both measures of the standard errors. The two variables jointly account for over 60% of cross-sectional variation in average portfolio returns. Thus, our results confirm Campbell and Vuolteenaho’s (2004) finding that the book-to-market effect reflects loadings on the discount-rate shock.

---

[14] Recent studies, e.g., Pastor and Veronesi (2003), Agarwal et al. (2004), and Mazzucato (2002), also find that growth stocks tend to have higher IV than value stocks.

[15] We focus on the modern sample because recent studies, e.g., Campbell Vuolteenaho (2004), Petkova and Zhang (2006), Ang and Chen (2006), Fama and French (2006), and Guo et al. (2005), show that CAPM explains the book-to-market effect in the early period 1926 to 1962.

Fama and French (1996) suggest that the value factor, HML, which is the return on a hedge portfolio that is long in high book-to-market stocks and short in low book-to-market stocks, proxies for changes in investment opportunities. If VWAIV is a measure of conditional discount-rate variance, we expect that it is closely correlated with realized value premium variance, V_HML. Indeed, the two variables have a correlation coefficient of over 90%. Moreover, if we replace VWAIV by V_HML in the cross-sectional regression, we find that V_HML has explanatory power very similar to that of VWAIV. For example, the second row of panel H, Table 3 shows that V_HML is positively and significantly priced in the cross-sectional regression, with a cross-sectional R^2 of about 58%. This result provides further support for the joint hypothesis that VWAIV is a measure of conditional discount-rate variance and HML is a proxy for the discount-rate shock.

Lastly, we directly investigate the relation between IVF and HML, which are both interpreted as proxies for changes in investment opportunities. As expected, the two variables are closely correlated with each other, with a correlation coefficient of over 45%. More importantly, if we replace HML by IVF in the Fama and French 3-factor model, the third row of panel H, Table 3 shows that IVF is significant at the 5% level according to both measures of the standard errors, with the cross-sectional R^2 of about 83%. For comparison, the last row of panel H presents the cross-sectional regression results using the original Fama and French 3-factor model, which accounts for about 80% of cross-sectional variation in average portfolio returns. In Figures 1 and 2, we plot the predicted returns versus the average realized returns for the models with IVF and HML, respectively. We find that IVF and HML have almost identical explanatory power for the 25 Fama and French portfolios. These results strongly suggest that the IV and book-to-market effects are closely related to each other because they both are proxies for changes in investment opportunities.

D. Estimating ICAPM Using Bivariate GARCH Models

Many early studies, e.g., Campbell (1987), Glosten et al. (1993), and Whitelaw (1994), document a negative relation between conditional stock market risk and return. Scruggs (1998) and Guo and Whitelaw (2006) suggest that the puzzling results reflect the fact that these authors did not control for the hedge component in Merton's (1973) ICAPM. For example, if IVF is a proxy for the discount-rate shock, we should uncover a positive risk-return relation in equation (4) after we control for the covariance with IVF. To address this issue, we jointly estimate the asset pricing equations for two risk factors:

$$(16)\qquad \begin{array}{l} R_{t+1} = \alpha_M + \gamma_{M,M}\sigma^2_{M,t} + \gamma_{M,I}\sigma_{M,I,t} + \upsilon_{M,t+1} \\ IVF_{t+1} = \alpha_I + \gamma_{I,M}\sigma_{M,I,t} + \gamma_{I,I}\sigma^2_{I,t} + \upsilon_{I,t+1} \end{array},$$

where $\sigma_{M,I,t}$ is conditional covariance between stock market returns and IVF and $\sigma^2_{I,t}$ is conditional variance of IVF. The ICAPM also imposes restrictions on the parameters in equation (16): $\alpha_M = \alpha_I = 0$, $\gamma_{M,M} = \gamma_{I,M}$, and $\gamma_{M,I} = \gamma_{I,I}$.

We estimate equation (16) using the asymmetric BEKK model proposed by Engle and Kroner (1995) as well as the more general asymmetric dynamic covariance (ADC) model by Kroner and Ng (1998). BEKK model is a special case of the ADC model; and we fail to reject the BEKK model relative to the ADC model using log likelihood ratio test. For brevity, we only report the results obtained from the BEKK model because a parsimonious specification allows us to estimate the parameters more precisely. Nevertheless, we find qualitatively similar results using the ADC model.

We estimate the BEKK model using the quasi-maximum likelihood (QML) method for the period February 1926 to December 2005, and report the results in Table 4. Bollerslev and Woodridge (1992) show that QML parameter estimates can be consistent, even though the conditional log-likelihood function assumes normality while stock returns are known to be skewed and leptokurtic. We also find similar results using the maximum likelihood estimation (MLE) method by assuming a *t* distribution or a normal distribution; for brevity, these results are not reported here but are available on request.

Row 1 of Table 4 presents the results for the unrestricted model. For the market return equation, we find that the risk-return coefficient, $\gamma_{M,M}$, is positive, with a point estimate of 4.30; moreover, it is also statistically significant at the 5% level. Similarly, the coefficient for the hedge component, $\gamma_{M,I}$ is positive and statistically significant at the 5% level. Overall, the constant term α_M is statistically insignificant, indicating that the variance and covariance terms explain a large portion of the average excess stock market return. We find similar results for the IVF equation. The prices of market risk ($\gamma_{I,M}$) and the discount-rate shock ($\gamma_{I,I}$) are positive and statistically significant at the 5% and 10% levels, respectively. However, the constant term α_I is significantly positive, indicating that IVF is a noisy measure for the discount-rate shock.

We impose the ICAPM restrictions in row 2 of Table 4. Again, the prices of market risk and discount-rate shock are positive; they are also statistically significant at the 1% level. Therefore, imposing the ICAPM restrictions allow us to estimate the risk prices more precisely. The point estimate for the price of market risk is about 5.90. This estimate, which can be interpreted as the coefficient of relative risk aversion, is plausible; for example, it falls within the range 1 to 10, as advocated by Mehra and Prescott (1985).

However, the log likelihood ratio test rejects the ICAPM restrictions possibly because IVF is a noisy measure for the discount-rate shock.

To summarize, controlling for the covariance with IVF helps us uncover a positive relation between conditional stock market risk and return. This result provides further support for the hypothesis that IVF is a proxy for the discount-rate shock in Campbell's ICAPM.

IV. Cross-Sectional IV Effects in G7 Countries

A. Returns on Quintile Portfolios Sorted on IV

As an additional out-of-sample test, this subsection investigates the cross-sectional IV effect in international stock markets. Table 5 presents the results for the value-weighted quintile portfolios sorted by the CAPM-based IV over the period March 1973 to December 2003 for G7 countries obtained from the Datastream data. We do not control for size here because the Datastream only includes stocks with large market capitalization and the other G7 countries have far fewer stocks than the U.S. For comparison, we also report the results for the U.S. using the CRSP data (panel H). The quintile 1 consists of the stocks with the lowest IV and the quintile 5 consists of the stocks with the highest IV. In column under title "1-5" we report the return difference between the quintiles 1 and 5. We also report the alphas for the return difference relative to a measure of the excess world stock market return obtained from Ken French at Dartmouth College.

For the U.S., panels G and H of Table 5 show that the CAPM-adjusted return difference is positive and statistically significant at the 5% level in both the CRSP and Datastream data. However, the cross-sectional IV effect is noticeably stronger for the

CRSP data than the Datastream data. The difference reflects the fact that the Datastream only include stocks with large market capitalization, while the CRSP includes all stocks.

Despite the potential bias in the Datastream data, Table 5 shows that the CAPM-adjusted return difference between the low and high IV quintiles is positive in all the other G7 countries except Italy. Moreover, the positive difference is statistically significant at the 5% level for Canada and Germany and significant at the 10% level for France. In the Japanese stock market, the annualized return difference is 5%, which is economically important albeit statistically insignificant.

We also investigate an early U.S. sample spanning the period February 1926 to June 1962, which has never been analyzed before because it just became available in 2006. The analysis thus provides another out-of-sample test for the cross-sectional IV effect documented by Ang et al. (2006a). Panel I of Table 5 shows that the return difference between the first and fifth quintiles is statistically insignificant; however, it becomes significant at the 10% level after we control for its loadings on the market risk.

To summarize, consistent with the evidence obtained from the modern U.S. sample, we also document a significant cross-sectional IV effect in many other G7 countries as well as an early U.S. sample. These results suggest that the cross-sectional IV effect is pervasive and cannot be only attributed to data mining.

B. Cross-Country Correlation of the CAPM-Based IV Effect

The empirical results in Section III suggest that the cross-sectional IV effect reflects systematic risk because IV proxies for loadings on the discount-rate shock. Therefore, if international equity markets are integrated, we expect that the cross-sectional IV effect has strong comovements among G7 countries. We address this issue in

Table 6, which presents the cross-country correlation of the return difference between the first and fifth IV quintiles, as reported in Table 5. We find that, expect for Germany, the trading profits of the other G7 countries are indeed closely correlated with their U.S. counterpart.

C. Relation between Cross-Sectional and Time-Series IV Effects

Lastly, we investigate the three ICAPM implications using the international data. Table 7 presents the OLS estimation results of regressing excess portfolio returns on U.S. MV and VWAIV.[16] The portfolio returns are originally constructed using stock returns denoted in local currencies. For comparison, we convert them into the returns in term of the U.S. dollar by applying the corresponding foreign exchange rates. Thus, the quarterly excess portfolio return used here is the difference between the portfolio return denoted in the U.S. dollar and the U.S. risk-free rate for all the G7 countries.

Table 7 shows that the results are similar to those reported in Tables 1 and 2 for the G7 countries except Germany. The coefficients are always positive for MV and negative for VWAIV; they are statistically significant at least at the 10% levels for most of the international portfolios. The coefficients on MV increase monotonically from low IV stocks to high IV stocks; by contrast, the coefficients on VWAIV decrease monotonically from low IV stocks to high IV stocks. As a result, the trading profit of buying low IV stocks and selling high IV stocks correlates negatively with MV but positively with VWAIV. Also, R^2 increases monotonically from low IV stocks to high

[16] Guo and Savickas (2005) find that the country-specific MV and VWAIV also have some predictive power for stock market returns in the other G7 countries. However, consistent with early studies, e.g., Harvey (1991), these variables become statistically insignificant after we control for their U.S. counterparts. We find similar results for returns on portfolios sorted on IV, which, for brevity, are omitted here but are available on request.

IV stocks. These results suggest that the IV effect in the international markets also reflect intertemporal pricing, which we formally investigate in Table 8.

Table 8 presents the cross-sectional regression results using 35 international portfolios sorted by the CAPM-based IV, with 5 portfolios for each of the G7 countries. Consistent with Campbell's ICAPM, panel A shows that VWAIV is positively and significantly priced, with the cross-sectional R^2 of about 78%.[17] The coefficient on MV is also positive, although it is statistically insignificant according to the Shanken-corrected standard errors. In panel B, we use the mimicking factor IVF along with the market and size factors. IVF is positively and significantly priced, and the associated cross-sectional R^2 is over 70%. Thus, the international evidence also strongly supports the hypothesis that the CAPM-based IV forecasts stock returns because it proxies for loadings on the discount-rate shock.

V. Conclusion

Recent authors find that in the modern U.S. sample the CAPM-based IV has negative effects on expected stock returns in both the time-series and cross-sectional regressions. This paper makes three contributions to this literature. First, we show that the cross-sectional IV effect is pervasive because it also exists in many other G7 countries as well as an early U.S. sample. Second, we propose a coherent explanation for both the time-series and cross-sectional IV effects. In particular, we suggest that high IV stocks

[17] The loadings on MV and VWAIV are likely to be less precisely estimated for international stock returns (Table 6) than U.S. stock returns (e.g., Table 1) for two reasons. First, the sample period is much shorter in Table 6 than in Table 1. Second, international stock returns are much more volatile than U.S. stock returns. To obtain precise estimates of the factor loadings, we restrict the intercept to be zero in the first-pass regression in panel A of Table 7. However, the results reported in panel B are not sensitive to such a restriction. This is because R^2 is much higher and thus factor loadings are much more precisely estimated in the regressions of portfolio returns on contemporaneous risk factors than in the forecasting regressions of portfolio returns on lagged variances.

have lower expected returns than low IV stocks because IV correlates negatively with loadings on the discount-rate shock in Campbell's ICAPM. Similarly, VWAIV is negatively related to future stock returns because it proxies for conditional discount-rate variance. Third, we formally test Campbell's ICAPM using both the U.S. and international data, and find that it does help explain the cross section of returns on the portfolios sorted by IV.

We also contribute to the empirical asset pricing literature by documenting a close relation between the IV effect and the prominent book-to-market effect. In particular, consistent with Campbell and Vuolteenaho (2004), we find that growth stocks have lower expected returns than value stocks because the former is more sensitive to the discount-rate shock. Our result thus sheds light on the ongoing debate about the book-to-market effect by suggesting that it does reflect intertemporal pricing.

Early studies, e.g., Campbell (1996), Campbell and Vuolteenaho (2004), and Petkova (2006), measure discount-rate shocks using innovations in state variables that forecast stock market returns. However, this approach is potentially sensitive to particular empirical specifications because economic theory doesn't stipulate which variables should be used to forecast stock market returns (e.g., Chen and Zhao, 2005). This paper shows that an alternative measure for discount-rate shocks—IVF, which is the return on a hedge portfolio that is long in low IV stocks and short in high IV stocks, appears to have good explanatory power for the cross section of stock returns. For example, it has explanatory power for the 25 Fama and French portfolios almost identical to that of the value factor. It might be interesting to further investigate its usefulness in future research.

Our analysis can be extended along several dimensions. First, the IV effects might be related to liquidity. Amihud and Mendelson (1989) document a close link between the cross-sectional IV effect and the liquidity effect, and Guo and Savickas (2006) find that aggregate liquidity measures have forecasting power similar to that of value-weighted average idiosyncratic variance. Similarly, Acharya and Pedersen (2005) find that liquidity shocks help explain the 25 Fama and French portfolios. A further investigation along this line appears to be warranted. Second, we need a general equilibrium model to understand economic forces behind the discount-rate shock. In particular, Guo (2004) develops a limited participation model in which discount rates are closely related to shareholders' liquidity conditions. A further investigation of the effect of the liquidity shock on the cross-sectional stock returns in his model seems an interesting exercise. Third, stock return predictability documented in this paper also should have important implications for portfolio management.

References

Acharya, V. and L. Pedersen, 2005, Asset Pricing with Liquidity Risk, Journal of Financial Economics, 77, 375-410.

Agarwal, D., S. Bharath, and S. Viswanathan, 2004, Technological Change and Stock Return Volatility: Evidence from eCommerce Adoptions, Unpublished Working paper, University of Michigan.

Amihud, Y. and H. Mendelson, 1989, The Effects of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns, Journal of Finance, 44, 479-486.

Ang, A., and J. Chen, 2006, CAPM over the Long Run: 1926-2001, Journal of Empirical Finance, forthcoming.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006a, the Cross-Section of Volatility and Expected Returns, Journal of Finance, 51, 259-299.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006b, High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence, Unpublished Working Paper, Columbia University.

Andersen, T., T. Bollerslev, F. Diebold, and P. Labys, 2003, Modeling and Forecasting Realized Volatility, Econometrica, 71, 579-625.

Asquith, P., P. Pathak, and J. Ritter, 2005, Short Interest, Institutional Ownership, and Stock Returns, Journal of Financial Economics, 78, 243-276.

Bali, T., N. Cakici, X. Yan, and Z. Zhang, 2005, Does Idiosyncratic Risk Really Matter? Journal of Finance, 60, 905-929.

Ball, R., 1978, Anomalies in Relationships between Securities' Yields and Yield-Surrogates, Journal of Financial Economics, 6, 103-126.

Basu, S., 1977, Investment Performance of Common Stocks in Relation to Their Price-

Earnings Ratios: A Test of the Efficient Market Hypothesis, Journal of Finance, 32, 663-682.

Basu, S., 1983, The Relationship Between Earnings Yield, Market Value, and Return for NYSE Common Stocks: Further Evidence, Journal of Financial Economics, 12, 129-156.

Berk, J., R. Green, and V. Naik, 1999, Optimal Investment, Growth Options and Security Returns, Journal of Finance, 54, 1153-1607.

Boehme, R., B. Danielsen, and S. Sorescu, 2006, Short Sale Constraints, Differences of Opinion, and Overvaluation, Journal of Financial and Quantitative Analysis, forthcoming.

Bollerslev, T., and J. Wooldridge, 1992, Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances, Econometric Reviews,11, 143-172.

Brennan, M., A. Wang, and Y. Xia, 2004, Estimation and Test of a Simple Model of Intertemporal Asset Pricing, Journal of Finance, 59, 1743-1775.

Campbell, J., 1987, Stock Returns and the Term Structure, Journal of Financial Economics, 18, 373-399.

Campbell, J., 1993, Intertemporal Asset Pricing Without Consumption Data, American Economic Review, 83, 487-512.

Campbell, J., 1996, Understanding risk and return, Journal of Political Economy, 104, 298-345.

Campbell, J., M. Lettau, B. Malkiel, and Y. Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, Journal of Finance, 56, 1-43.

Campbell, J. and R. Shiller, 1998, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, Review of Financial Studies, 1, 195-228.

Campbell, J., T. Vuolteenaho, 2004, Bad Beta, Good Beta, American Economic Review, 94, 1249-1275.

Chen, J., H. Hong, and J. Stein, 2002, Breadth of ownership and stock returns, Journal of Financial Economics, 66, 171-205.

Chen, L., and X. Zhao, 2005, Return Decomposition, Unpublished Working Paper, Michigan State University.

Diether, K., C., Malloy, and A. Scherbina, 2002, Differences of Opinion and the Cross Section of Stock Returns, Journal of Finance, 57, 2113-2141.

Doukas, A., C. Kim, and C. Pantzalis, 2006, Divergence of Opinion and Equity Returns, Journal of Financial and Quantitative Analysis, forthcoming.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2002, Is Information Risk a Determinant of Asset Returns? Journal of Finance, 57, 2185-2221.

Engle, R., and K. Kroner, 1995, Multivariate Simultaneous Generalized ARCH, Econometric Theory, 11, 122-150.

Fama, E. and K. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics, 33, 3-56.

Fama, E. and K. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, Journal of Finance, 51, 55-84.

Fama, E. and K. French, The Value Premium and the CAPM, Journal of Finance, forthcoming.

Fama E. and J. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, Journal of Political Economy, 81, 607-36.

Fu, F., 2005, Idiosyncratic Risk and the Cross-Section of Expected Stock Returns, Unpublished Working Paper, University of Rochester.

Ghysels, E., P. Santa-Clara, and R. Valkanov, 2005, There Is a Risk-Return Tradeoff After All, Journal of Financial Economics, 76, 509-548.

Glosten, L, R. Jagannathan, and D. Runkle, 1993, On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, Journal of Finance, 48, 1779-1801

Gomes, J., L. Kogan, and L. Zhang, 2003, Equilibrium Cross Section of Returns, Journal of Political Economy, 111, 693-732.

Goyal, A. and P. Santa-Clara, 2003, Idiosyncratic Risk Matters! Journal of Finance, 58, 975-1007.

Graham, B. and D. Dodd, 1934, Security Analysis, New York: McGraw Hill.

Guo, H., 2004, Limited Stock Market Participation and Asset Prices in a Dynamic Economy, Journal of Financial and Quantitative Analysis, 39, 495-516.

Guo, H. and R. Savickas, 2005, Average Idiosyncratic Volatility in G7 Countries, Unpublished Working Paper, Federal Reserve Bank of St. Louis.

Guo, H. and R. Savickas, 2006, Idiosyncratic Volatility, Stock Market Volatility, and Expected Stock Returns, Journal of Business and Economic Statistics, 24, 43-56.

Guo, H. and R. Whitelaw, 2006, Uncovering the Risk-Return Relation in the Stock Market, Journal of Finance, forthcoming.

Guo, H., R. Savickas, Z. Wang, and J. Yang, 2005, Is the Value Premium a Proxy for Time-Varying Investment Opportunities: Some Time Series Evidence, Unpublished Working Paper, the Federal Reserve Bank of St. Louis.

Harvey, Campbell, 1991, The World Price of Covariance Risk, Journal of Finance, 46, 111-157.

Kroner, K., and V. Ng, 1998, Model Asymmetric Comovements of Asset Returns, Review of Financial Studies, 11, 817-844.

Lettau, M. and S. Ludvigson, 2001, Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying, Journal of Political Economy, 109, 1238-1287.

Lettau, M. and J. Wachter, 2006, Why is Long-horizon Equity Less Risky? A Duration-based Explanation of the Value Premium, Journal of Finance, forthcoming.

Levy, H., 1978, Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio, American Economic Review, 68, 643-58.

Lakonishok, J., A. Shleifer, and R. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, Journal of Finance, 49, 1541-1578.

Mazzucato, M., 2002, The PC industry: New Economy or Early Life-Cycle?, Review of Economic Dynamics 5, 318–345.

MacKinlay, C., 1995, Multifactor Models Do Not Explain Deviations from the CAPM, Journal of Financial Economics, 99, 928-956.

Malkiel, B. and Y. Xu, 2002, Idiosyncratic Risk and Security Returns, Unpublished Working Paper, University of Texas at Dallas.

Mehra, R., and E. Prescott, 1985, The Equity Premium: A Puzzle, Journal of Monetary Economics, 15, 145-161.

Merton, R., 1973, An Intertemporal Capital Asset Pricing Model, Econometrica, 41, 867-887.

Merton, R., 1980, On Estimating the Expected Return on the Market: An Exploratory Investigation, Journal of Financial Economics, 8, 323-61.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information, Journal of Finance, 42, 483-510.

Miller, E., 1977, Risk, Uncertainty, and Divergence of Opinion, Journal of Finance, 32, 1151-1168.

Pastor, L. and P. Veronesi, 2003, Stock Valuation and Learning about Profitability, Journal of Finance, 58, 1749-1790.

Petkova, R., 2006, Do the Fama-French Factors Proxy for Innovations in Predictive Variables? Journal of Finance, forthcoming.

Petkova, R., and L. Zhang, 2005, Is Value Riskier than Grow? Journal of Financial Economics, 78, 187-202.

Rosenberg, B., K. Reid, and R., Lanstein, 1985, Persuasive Evidence of Market Inefficiency, Journal of Portfolio Management, 11, 9-17.

Scruggs, J., 1998, Resolving the Puzzling Intertemporal Relation Between the Market Risk Premium and Conditional Market Variance: A Two Factor Approach, Journal of Finance, 53, 575-603.

Shalen, C., 1993, Volume, Volatility, and the Dispersion of Beliefs, Review of Financial Studies, 6, 405-434.

Shanken, J., 1992, On the Estimation of Beta-Pricing Models, Review of Financial Studies, 5, 1-33.

Spiegel, M. and X. Wang, 2005, Cross-sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk, Unpublished Working Paper, Yale University.

Whitelaw, R., 1994, Time Variations and Covariations in the Expectation and Volatility of Stock Market Returns, Journal of Finance, 49, 515-541.

Zhang, L., 2005, The Value Premium, Journal of Finance, 60, 67-103.

Table 1 Portfolios Sorted by Size and IV: Modern Sample

	S1(smallest)	S2	S3	S4	S5(largest)
	Panel A Sample Average Excess Returns				
IV1(lowest)	0.031	0.031	0.030	0.024	0.014
IV2	0.043	0.039	0.034	0.031	0.017
IV3	0.048	0.031	0.033	0.030	0.016
IV4	0.045	0.021	0.023	0.024	0.016
IV5(highest)	0.027	-0.013	-0.013	-0.002	0.010
	Panel B Alpha Relative to CAPM				
1-5	**0.019**	**0.057**	**0.055**	**0.039**	**0.015**
	(1.751)	**(6.918)**	**(7.460)**	**(5.582)**	**(2.545)**
	Panel C Parameter Estimates MV				
IV1(lowest)	**6.290**	**6.060**	**5.734**	**4.907**	**4.546**
IV2	**13.872**	**11.513**	**9.462**	**7.671**	**7.789**
IV3	**18.593**	**15.038**	**13.017**	**10.022**	**10.337**
IV4	**21.267**	**19.744**	**16.496**	**14.235**	**12.933**
IV5(highest)	**25.343**	**19.821**	**18.368**	**18.212**	**17.642**
	Panel D Parameter Estimates VWAIV				
IV1(lowest)	-1.226	-0.985	-0.698	-0.646	**-1.256**
IV2	**-2.781**	**-2.204**	**-1.731**	**-1.424**	**-2.102**
IV3	**-3.526**	**-3.157**	**-2.562**	**-2.288**	**-2.791**
IV4	**-4.811**	**-4.765**	**-3.985**	**-3.888**	**-4.200**
IV5(highest)	**-6.436**	**-5.673**	**-5.011**	**-5.487**	**-5.913**
	Panel E T-Statistics MV				
IV1(lowest)	1.981	2.293	2.121	1.765	2.277
IV2	2.891	2.897	2.666	2.203	3.120
IV3	3.104	3.136	2.848	2.537	3.242
IV4	2.894	3.082	3.046	3.264	4.216
IV5(highest)	2.912	2.925	3.021	3.238	4.142
	Panel F T-Statistics VWAIV				
IV1(lowest)	-1.588	-1.638	-1.030	-1.008	-2.204
IV2	-2.012	-2.323	-1.975	-1.714	-3.485
IV3	-1.795	-2.453	-2.031	-2.279	-3.912
IV4	-2.135	-2.840	-2.426	-3.017	-4.325
IV5(highest)	-2.539	-2.921	-2.780	-2.769	-4.172
	Panel G R^2				
IV1(lowest)	0.000	0.014	0.027	0.018	0.028
IV2	0.046	0.050	0.048	0.029	0.066
IV3	0.076	0.068	0.066	0.052	0.099
IV4	0.067	0.091	0.083	0.085	0.137
IV5(highest)	0.066	0.067	0.077	0.108	0.187

Panel H Fama and MacBeth (1973) Cross-Sectional Regressions

Constant	MKT	SMB	IVF	VWAIV	MV	R^2
0.019				**0.020**	**0.005**	0.628
(3.013)				(5.285)	(3.462)	
[1.751]				[3.163]	[2.054]	
-0.014	**0.026**	**0.046**	**0.025**			0.535
(-1.617)	(2.311)	(5.956)	(2.773)			
[-1.089]	[1.731]	[4.467]	[2.690]			

Note: We first sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into five portfolios by the CAPM-based IV. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile portfolio of stocks with lowest IV and IV5 is the quintile portfolio of stocks with the highest IV. We construct all the portfolios with the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. We regress the one-quarter-ahead excess portfolio return on MV and VWAIV and report the OLS estimation results in panels B to G. Panel H reports the Fama and MacBeth (1973) cross-sectional regression results. We assume that factor loadings are constant and estimate them using the full sample. We report Fama and MacBeth t-statistics in parentheses and Shanken (1992) corrected t-statistics in squared brackets. MV is realized stock market variance; VWAIV is value-weighted average idiosyncratic variance; MKT is the excess stock market return; SMB is the size factor; HML is the value factor; IVF is the equal-weighted average of the return difference between IV1 and IV5 across all size quintiles. The sample spans the period 1964:Q1 to 2005:Q4. Bold denotes significance at the 10% level; for the cross-sectional regressions, we use the Shanken-corrected standard errors to determine the significance level.

Table 2 Portfolios Sorted on Size and IV: Full Sample

	S1(smallest)	S2	S3	S4	S5(largest)
Panel A Sample Average Excess Returns					
IV1(lowest)	0.046	0.039	0.035	0.028	0.020
IV2	0.056	0.045	0.037	0.031	0.022
IV3	0.057	0.043	0.039	0.033	0.022
IV4	0.051	0.032	0.029	0.032	0.021
IV5(highest)	0.050	0.004	0.006	0.014	0.016
Panel B Alpha Relative to CAPM					
1-5	**0.016**	**0.049**	**0.044**	**0.031**	**0.017**
	(1.746)	**(9.013)**	**(9.069)**	**(6.293)**	**(4.117)**
Panel C Parameter Estimates MV					
IV1(lowest)	6.131	3.778	2.447	1.169	1.417
IV2	9.103	5.205	3.393	2.274	1.833
IV3	9.275	7.083	4.548	2.862	2.396
IV4	9.763	8.119	4.850	5.823	4.040
IV5(highest)	11.507	6.707	**6.879**	6.722	**5.058**
Panel D Parameter Estimates VWAIV					
IV1(lowest)	**-2.259**	-1.352	-0.681	-0.469	**-0.906**
IV2	-2.654	-1.531	-1.001	-0.687	**-1.129**
IV3	-2.509	-1.457	-1.461	-0.865	**-1.329**
IV4	-2.818	**-2.912**	**-2.304**	**-2.249**	**-2.140**
IV5(highest)	**-3.732**	**-3.351**	**-3.299**	**-3.350**	**-3.064**
Panel E T-Statistics MV					
IV1(lowest)	1.498	1.260	0.999	0.616	0.850
IV2	1.511	1.321	1.016	0.909	1.015
IV3	1.449	1.278	1.241	0.905	1.069
IV4	1.329	1.551	1.281	1.495	1.562
IV5(highest)	1.474	1.546	1.690	1.636	1.673
Panel F T-Statistics VWAIV					
IV1(lowest)	-1.841	-1.456	-0.875	-0.776	-1.689
IV2	-1.490	-1.327	-1.008	-0.911	-2.057
IV3	-1.270	-0.990	-1.210	-0.927	-2.174
IV4	-1.356	-1.907	-1.790	-1.857	-2.715
IV5(highest)	-1.723	-2.402	-2.425	-2.359	-2.750
Panel G R^2					
IV1(lowest)	0.043	0.025	0.022	0.001	0.005
IV2	0.053	0.032	0.014	0.011	0.006
IV3	0.044	0.043	0.024	0.008	0.012
IV4	0.035	0.045	0.022	0.029	0.025
IV5(highest)	0.036	0.023	0.032	0.035	0.038

Panel H Fama and MacBeth (1973) Cross-Sectional Regressions

Constant	MKT	SMB	IVF	VWAIV	MV	R^2
0.030				**0.021**	**0.008**	0.813
(5.537)				(8.092)	(4.102)	
[3.631]				[5.565]	[2.769]	
0.007	0.013	**0.047**	**0.022**			0.826
(1.043)	(1.454)	(6.072)	(3.511)			
[0.833]	[1.280]	[5.100]	[3.400]			

Note: We first sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into five portfolios by the CAPM-based IV. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile portfolio of stocks with lowest IV and IV5 is the quintile portfolio of stocks with the highest IV. We construct all the portfolios with the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. We regress the one-quarter-ahead excess portfolio return on MV and VWAIV and report the OLS estimation results in panels B to G. Panel H reports the Fama and MacBeth (1973) cross-sectional regression results. We assume that factor loadings are constant and estimate them using the full sample. We report Fama and MacBeth t-statistics in parentheses and Shanken (1992) corrected t-statistics in squared brackets. MV is realized stock market variance; VWAIV is value-weighted average idiosyncratic variance; MKT is the excess stock market return; SMB is the size factor; HML is the value factor; IVF is the equal-weighted average of the return difference between IV1 and IV5 across all size quintiles. The sample spans the period 1926:Q4 to 2005:Q4. Bold denotes significance at the 10% level; for the cross-sectional regressions, we use the Shanken-corrected standard errors to determine the significance level.

Table 3 Fama and French 25 Portfolios Sorted on Size and Book-to-Market

	S1(smallest)	S2	S3	S4	S5(largest)
Panel A Sample Average Excess Returns					
BM1(lowest)	0.012	0.015	0.015	0.018	0.013
BM2	0.028	0.022	0.024	0.017	0.015
BM3	0.029	0.030	0.024	0.024	0.015
BM4	0.036	0.032	0.028	0.027	0.018
BM5(highest)	0.039	0.034	0.033	0.028	0.018
Panel B Alpha Relative to CAPM					
5-1	**0.035**	**0.025**	**0.024**	**0.014**	0.008
	(6.164)	**(4.295)**	**(3.933)**	**(2.359)**	(1.512)
Panel C Parameter Estimates MV					
BM1(lowest)	**16.118**	**14.660**	**12.881**	**10.820**	**8.958**
BM2	**12.434**	**11.209**	**9.865**	**9.078**	**7.774**
BM3	**10.265**	**7.790**	**7.657**	**8.836**	**5.965**
BM4	**9.025**	**7.678**	**7.742**	**7.919**	**6.722**
BM5(highest)	**10.933**	**8.801**	**7.647**	**8.184**	**5.724**
Panel D Parameter Estimates VWAIV					
BM1(lowest)	**-4.301**	**-3.959**	**-3.833**	**-2.936**	**-2.901**
BM2	**-2.498**	**-2.286**	**-2.388**	**-1.860**	**-1.993**
BM3	**-1.767**	**-1.575**	**-1.660**	**-1.888**	**-1.497**
BM4	-1.369	**-1.511**	**-1.620**	**-1.599**	**-1.456**
BM5(highest)	**-2.236**	**-1.868**	-1.360	**-1.818**	**-1.726**
Panel E T-Statistics MV					
BM1(lowest)	3.057	3.359	3.355	3.050	3.399
BM2	2.621	2.701	2.824	2.865	2.872
BM3	2.622	2.234	2.481	2.924	2.549
BM4	2.465	2.121	2.102	2.598	2.482
BM5(highest)	2.419	2.049	1.984	1.995	1.805
Panel F T-Statistics VWAIV					
BM1(lowest)	-2.500	-2.959	-2.886	-2.391	-3.877
BM2	-1.940	-2.173	-3.007	-2.353	-3.232
BM3	-1.901	-1.886	-2.205	-2.450	-2.231
BM4	-1.503	-1.806	-1.869	-2.090	-1.858
BM5(highest)	-2.080	-1.893	-1.548	-1.918	-2.141
Panel G R^2					
BM1(lowest)	0.065	0.077	0.083	0.071	0.076
BM2	0.050	0.063	0.052	0.056	0.055
BM3	0.040	0.030	0.036	0.048	0.040
BM4	0.034	0.026	0.032	0.036	0.046
BM5(highest)	0.034	0.021	0.022	0.040	0.024

Panel H Fama and MacBeth (1973) Cross-Sectional Regressions

Constant	MKT	HML	SMB	IVF	VWAIV	MV	V_HML	R^2
0.022					**0.015**	0.004		0.612
(3.218)					(3.721)	(2.196)		
[2.218]					[2.617]	[1.534]		
0.021						0.004	**0.002**	0.579
(3.163)						(2.300)	(3.904)	
[2.081]						[1.535]	[2.620]	
0.038	-0.022		**0.009**	**0.023**				0.826
(3.222)	(-1.698)		(2.073)	(2.066)				
[2.893]	[-1.562]		[2.068]	[1.985]				
0.031	-0.016	**0.014**	**0.008**					0.791
(2.538)	(-1.121)	(3.021)	(1.722)					
[2.392]	[-1.070]	[3.011]	[1.717]					

Note: We use the 25 Fama and French portfolios sorted by size and book-to-market. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. BM1 is the quintile portfolio of stocks with the lowest book-to-market ratio and BM5 is the quintile portfolio of stocks with the highest book-to-market ratio. All the portfolios are constructed using the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. We regress the one-quarter-ahead excess portfolio return on MV and VWAIV and report the OLS estimation results in panels B to G. Panel H reports the Fama and MacBeth (1973) cross-sectional regression results. We assume that factor loadings are constant and estimate them using the full sample. We report Fama and MacBeth t-statistics in parentheses and Shanken (1992) corrected t-statistics in squared brackets. MV is realized stock market variance; VWAIV is value-weighted average idiosyncratic variance; MKT is the excess stock market return; SMB is the size factor; HML is the value factor; IVF is the equal-weighted average of the return difference between IV1 and IV5 across all size quintiles. The sample spans the period 1964:Q1 to 2005:Q4. Bold denotes significance at the 10% level; for the cross-sectional regressions, we use the Shanken-corrected standard errors to determine the significance level.

Table 4 Estimating ICAPM Using Bivariate Asymmetric BEKK Models

	MKT Equation			IVF Equation			LL
	α_M	$\gamma_{M,M}$	$\gamma_{M,I}$	α_I	$\gamma_{I,M}$	$\gamma_{I,I}$	
1	0.004	**4.298**	**3.870**	**0.010**	**7.456**	**2.681**	3478.510
	(1.596)	(2.259)	(2.142)	(6.016)	(2.259)	(1.947)	
2		**5.902**	**4.543**		**5.902**	**4.543**	3430.790
		(3.769)	(4.013)		(3.769)	(4.013)	

Note: The Table reports the estimation results of ICAPM with asymmetric BEKK model proposed by Engle and Kroner (1995):

$$(16)\qquad \begin{aligned} R_{t+1} &= \alpha_M + \gamma_{M,M}\sigma^2_{M,t} + \gamma_{M,I}\sigma_{M,I,t} + \upsilon_{M,t+1} \\ IVF_{t+1} &= \alpha_I + \gamma_{I,M}\sigma_{M,I,t} + \gamma_{I,I}\sigma^2_{I,t} + \upsilon_{I,t+1} \end{aligned},$$

where R_{t+1} is the excess stock market return and IVF_{t+1} is the return on a hedge portfolio that is long in low IV stocks and short in high IV stocks. We estimate the BEKK model using the quasi-maximum likelihood method. Row 1 is the unrestricted ICAPM. In row 2, we impose the ICAPM restrictions on the parameters: $\alpha_M = \alpha_I = 0$, $\gamma_{M,M} = \gamma_{I,M}$, and $\gamma_{M,I} = \gamma_{I,I}$. The sample spans the period February 1926 to December 2005. T-statistics are reported in parentheses. Bold denotes significance at the 10% level.

Table 5 Return on Quintile Portfolios Sorted on IV in G7 Countries

1(lowest)	2	3	4	5(highest)	1-5	T-stat	Alpha	T-stat
Panel A Canada								
0.010	0.010	0.006	0.001	-0.003	**0.013**	2.309	**0.014**	2.572
Panel B France								
0.015	0.013	0.013	0.008	0.009	0.006	1.394	**0.008**	1.857
Panel C Germany								
0.011	0.008	0.006	0.009	0.004	**0.006**	2.526	**0.006**	2.422
Panel D Italy								
0.013	0.012	0.012	0.012	0.014	-0.001	-0.275	-0.000	-0.122
Panel E Japan								
0.005	0.007	0.007	0.006	0.002	0.004	1.230	0.004	1.436
Panel F U.K.								
0.015	0.013	0.013	0.014	0.014	0.001	0.244	0.002	0.717
Panel G U.S.								
0.010	0.011	0.012	0.010	0.003	0.007	1.576	**0.009**	2.252
Panel H U.S (CRSP)								
0.011	0.011	0.011	0.008	0.000	**0.011**	2.593	**0.013**	3.347
Panel I U.S. (CRSP, February 1926 to June 1962)								
0.010	0.010	0.011	0.010	0.008	0.001	0.379	**0.006**	1.923

Note: The table reports returns on quintile portfolios equally sorted by the CAPM-based IV. Unless otherwise indicated, we use Datastream data over the period March 1973 to December 2003. The first quintile includes stocks with the highest IV and the fifth quintile includes stocks with the lowest IV. Column under name "1-5" reports the return difference between the first and fifth IV quintile. Column "Alpha" reports the alpha of the return difference between the first and fifth IV quintiles relative to a measure of the world excess stock market return. Bold denotes significance at the 10% level.

Table 6 Cross-Country Correlation of the IV Effect

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	U.S. (CRSP)
Canada	1.00							
France	0.31	1.00						
Germany	0.17	0.01	1.00					
Italy	0.06	0.26	-0.03	1.00				
Japan	0.07	0.11	-0.05	0.18	1.00			
U.K.	0.16	0.32	0.01	0.26	0.15	1.00		
U.S.	0.28	0.41	-0.03	0.28	0.30	0.40	1.00	
U.S. (CRSP)	0.28	0.42	-0.01	0.28	0.28	0.44	0.94	1.00

Note: The table reports the correlation coefficients of the return difference between the quintile of stocks with the highest CAPM-based IV and the quintile of stocks with the lowest IV among G7 countries. Unless otherwise indicated, we use the Datastream data. The monthly data span the period March 1973 to December 2003.

Table 7 Loadings on U.S. Aggregate and Idiosyncratic Stock Variances

	Const	T-stat	MV	T-stat	VWAIV	T-stat	R^2
			Panel A Canada				
1(lowest)	0.001	0.068	**5.708**	2.661	-0.929	-1.271	0.013
2	0.014	0.908	**8.017**	2.843	**-2.129**	-2.017	0.028
3	**0.036**	1.743	**11.881**	2.862	**-4.772**	-3.447	0.100
4	0.002	0.115	**16.289**	4.099	**-5.271**	-4.392	0.098
5(highest)	-0.039	-1.228	**30.601**	1.839	**-7.248**	-2.260	0.153
1-5	0.039	1.294	-25.027	-1.443	**6.424**	2.001	0.111
			Panel B France				
1(lowest)	**0.050**	2.829	**7.455**	1.764	**-2.921**	-3.127	0.026
2	**0.042**	2.272	6.695	1.405	**-2.558**	-2.504	0.006
3	0.033	1.639	**11.653**	2.203	**-3.546**	-2.869	0.043
4	**0.054**	2.645	**14.355**	2.622	**-5.799**	-4.651	0.111
5(highest)	0.016	0.714	**21.155**	3.055	**-5.764**	-4.032	0.107
1-5	**0.034**	1.964	**-13.045**	-2.549	**2.661**	2.043	0.065
			Panel C Germany				
1(lowest)	**0.034**	2.216	**5.775**	1.695	**-2.009**	-2.369	0.008
2	**0.037**	2.225	2.506	0.838	-1.572	-1.634	-0.005
3	**0.030**	1.778	3.538	0.752	-1.932	-1.598	0.010
4	**0.034**	1.884	5.488	1.081	**-2.180**	-1.977	0.005
5(highest)	0.010	0.599	5.347	1.043	-1.668	-1.529	0.001
1-5	**0.025**	1.879	0.616	0.175	-0.442	-0.491	-0.020
			Panel D Italy				
1(lowest)	**0.036**	1.676	6.068	1.641	**-2.447**	-2.591	0.024
2	**0.042**	1.792	**7.520**	1.871	**-3.195**	-3.376	0.032
3	0.040	1.554	4.711	1.078	**-2.503**	-2.361	-0.004
4	**0.043**	1.756	**7.022**	1.737	**-3.108**	-3.255	0.013
5(highest)	**0.047**	1.805	**9.970**	1.935	**-3.834**	-2.945	0.027
1-5	-0.012	-0.643	-3.556	-1.154	1.299	1.267	-0.021
			Panel E Japan				
1(lowest)	0.026	1.452	0.931	0.316	-0.852	-1.023	-0.005
2	**0.040**	2.153	4.135	1.303	**-2.175**	-2.498	0.007
3	**0.038**	2.013	3.215	0.903	**-1.944**	-1.935	0.013
4	0.030	1.503	**8.093**	2.020	**-2.941**	-2.666	0.034
5(highest)	0.021	0.928	**9.426**	1.734	**-3.397**	-2.471	0.024
1-5	0.005	0.356	**-8.560**	-2.500	**2.595**	2.823	0.132
			Panel F U.K.				
1(lowest)	**0.035**	2.225	5.067	0.954	**-1.663**	-1.758	-0.002
2	0.020	1.221	7.461	1.068	-1.818	-1.457	-0.004
3	**0.037**	2.189	7.580	1.094	**-2.633**	-2.206	0.014
4	**0.047**	2.732	10.163	1.332	**-3.827**	-2.808	0.051
5(highest)	**0.058**	2.605	12.750	1.575	**-4.843**	-2.973	0.056
1-5	-0.023	-1.527	**-7.609**	-1.834	**3.167**	2.902	0.043
			Panel G U.S.				
1(lowest)	**0.021**	1.959	**4.307**	2.200	**-1.281**	-2.339	0.021
2	0.020	1.656	**7.899**	2.679	**-2.228**	-3.205	0.052
3	**0.028**	1.869	**11.054**	3.284	**-3.388**	-3.758	0.095
4	0.024	1.278	**16.713**	3.614	**-5.089**	-3.621	0.144
5(highest)	-0.005	-0.207	**23.198**	3.589	**-6.559**	-3.451	0.166
1-5	0.026	1.302	**-18.891**	-3.683	**5.277**	3.232	0.170

Note: The table reports the OLS estimation results of regressing excess portfolio returns on U.S. realized stock market variance (MV) and U.S. CAPM-based value-weighted average realized idiosyncratic variance (VWAIV). All returns are denoted in the U.S. dollar. The quarterly data span the period 1973:Q3 to 2003:Q4. Bold denotes significance at the 10% level.

Table 8 Fama and MacBeth (1973) Cross-Sectional Regressions

Const	MKT	HML	SMB	IVF	VWAIV	MV	V_HML	R^2
Panel A Idiosyncratic Variance Model								
0.014					**0.022**	0.006		0.775
(1.396)					(3.634)	(2.343)		
[0.802]					[2.126]	[1.380]		
Panel B IV Factor Model								
0.006	0.019		-0.018	**0.037**				0.721
(0.424)	(1.145)		(-1.278)	(2.353)				
[0.351]	[0.987]		[-1.090]	[2.128]				

Note: In this table, we report the Fama and MacBeth (1973) cross-Sectional regression results using 35 international portfolios sorted by the CAPM-based IV, with 5 portfolios for each of the G7 countries. We assume that loadings on risk factors are constant and estimate them using the full sample. Fama and MacBeth t-statistics are reported in parentheses and the Shanken (1992) corrected t-statistics are in square brackets. The quarterly data span the period 1973:Q2 to 2003:Q4. Bold denotes significance at the 10% level according to both Fama and MacBeth and Shanken-corrected t-statistics.

Figure 1 Explaining 25 Fama and French Portfolios with HML

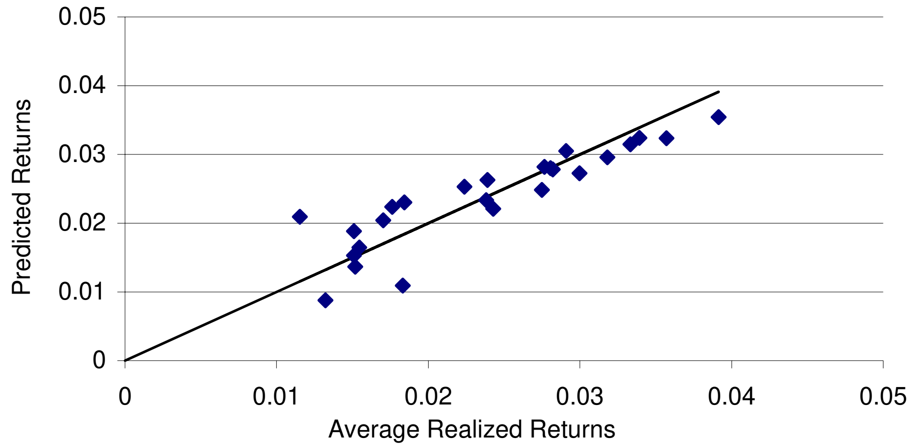

Figure 2 Explaining 25 Fama and French Portfolios with IVF